# A PRODUCTION COST MODEL FOR LONG-TERM POWER PRICE CORRELATION FORECASTING

A Thesis

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## ABSTRACT

Medium and long-term electricity price forecasting in deregulated power markets is important to market operators and participants. Lack of access to detailed system information and uncertainty in changing market pressures including fuel price, generation additions and retirements, changes in demand, and transmission additions compound the difficulties of accurately predicting market dynamics. Increasing penetration of renewable resources can affect the market in unpredictable ways. We seek to develop a highly parallelizable production cost model capable of forecasting long-term price dynamics under a variety of market scenarios. Using this framework, uncertainty in inter- and intra-regional market dynamics can be quantified using Monte-Carlo simulation. The framework was tested using a reduced model of the ERCOT power market. Estimation methods were tested for generator heat rate and intra-regional wind capacity factor, and compared the results to historical LMP data for the year 2011. Areas for future improvement were identified for the wind capacity factor estimation method, as well as the model as a whole moving forward.

## BIOGRAPHICAL SKETCH

Brandon Bass hails from New City, NY. His research focus is on characterizing long-term inter- and intra-market power price correlations, utilizing a partnership between academia and industry. He graduated Cornell University with a B.S. in Environmental Engineering and a minor in Business. Before his current research, Brandon worked with Professor Andersons group to characterize the effect of uncertainty on mass and energy in the switchgrass-to-ethanol process. In addition, Brandon has conducted independent research on renewable energy investment policy, and coauthored a bioreactor design paper which won 2nd place in the NABEC Student Design Competition. Brandon has professional experience in power systems analysis, environmental regulation, and project finance. He has worked in tandem with non-profit organizations at the 2012 United Nations Framework Conference on Climate Change in Doha, Qatar. Brandon was a teaching assistant for BEE 4010: Renewable Energy Systems, and has served as project leader, co-president, and co-founder for organizations on campus including Sustainable Enterprise Association, Society for Social Entrepreneurship and Collaborative Action, and American Academy of Environmental Engineers, respectively. Brandon will be working as a Senior Consultant for Navigant Consulting's energy practice starting February 2014.

This document is dedicated to my parents and panacea, Eugene and Sharon Bass.

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CHAPTER 1

# INTRODUCTION

Accurately forecasting electricity price is important to power market participants and operators. Market participants need to forecast price movements in order to maximize their profits, hedge against risks of price volatility in spot markets, ensure investment recovery. Market operators use forecasted prices to predict cases of market power and gaming behaviors, as well as to plan generation, transmission, and distribution [18].

In recent years, the electric power industry has undergone significant changes. A movement towards competitive power price settlement in a centralized marketplace has reopened questions on how to best forecast electricity demand and price. Load forecasting has reached advanced stages of development. There are load forecasting algorithms presently available with mean absolute percentage error (MAPE) below 3% [1] [20] . Price-forecasting techniques are still in their early stages of maturity [2]. This is due in part to the complex characteristics of price-curves, such as high frequency, non-constant mean and variance, multiple seasonality, calendar effect, high level of volatility, and high percentage of unusual price movements. The electricity market has qualities which distinguish it from other commodities. It cannot be appreciably stored, and requires constant balance between supply and demand, and exhibits inelastic demand over short time periods [7]. In a deregulated market, power price forecasting is essential for market participants survival. What follows is a brief review of the various approaches to power price forecasting. We then assess the current state of medium to long-term forecasting.

## 1.1 Simulation Models

Several authors have proposed clasifications of various forecasting methods. In the following sections, we briefly discuss concepts, strengths, weaknesses, and applications behind two major categories of forecasting: simulation models and statistical models. We then discuss the current state of medium and long-term forecasting as it relates to our objective.

### 1.1.1 Game Theory Models

Deregulated market participants face significant uncertainty and complexity in formulating their strategic plans. This arises not only because of the complexity of the sector, but because "many of the participants in the sector are new and have unclear motives and no history to use as a basis for predicting their behavior in the new market place"[17]. Market participants have complicated motives and operate in a system with complex feedbacks. Against this background, system operators are tasked with creating policies which allow reasonable returns on investment while fostering a system aligned with the interests of the ratepayers. The focus in game theory models is examining the impact of uncertainty and scenarios on the bids submitted to the power pool administrator. These bids consist of a capacity at a specific bid price for a specific time period. The details regarding when the bids are submitted and how long they remain in effect until a new bid must be submitted, vary from market to market. A system administrator then prepares a schedule to meet total projected system demand at minimum cost.

Game theory models allow for the analysis of situations where bids depart from marginal cost. There exist many situations which can prevent power markets from being fully competitive. An oligopolistic market economy consisting of several dominant firms in a power network can reduce the validity of the price-taker assumption. System topology can create anomalies and bottlenecks, resulting in arbitrage opportunities. Other considerations are auction design, transmission pricing, the ability to bypass auctions via bilateral transactions, whether firms are vertically integrated, and market power mitigations (such as must run provisions) [15]. Degrees of interaction among rival firms, spanning from intense competition to collusion, can have a significant impact on the submitted bid prices and market evolution. Many modeling studies of market power in electricity markets have already been undertaken. Under many scenarios, market power can have an impact on bids, which can impact the resulting market clearing prices. Although game theory models provide useful insights for market participants, they are based on the assumption that all market participants act strategically, and generally, they do not provide accurate predictions compared to the data-driven methods [20].

### 1.1.2 Production Cost Models

Production Cost Models are designed to calculate a generation system's production costs considering expected load pattern, heat rate curves of different generators, fuel costs, economic dispatch, and unit commitment schedules. Transmission constraints information is included to incorporate spatial considerations, resulting in locational marginal price (LMP). In some models, additional effects of ancillary services and emission allowance markets on energy prices have also been included. To ascertain the systematic effect of price drivers like generation and load levels on price variability, Monte-Carlo simulations are usually performed [3]. Monte-Carlo methods can provide a tremendous amount of flexibility, allowing a system planner to depart from the standard assumptions present in the analytical models and explore assumptions conforming to more realistic or pressing scenarios.

The most frequently used model of production costing is the one due to Baleriaux et al. and Booth. This model estimates the expected production costs by using the load duration curve (LDC) in place of the chronological sequence of loads and the steady-state unavailability of the individual units. The long-run proportion of time that a given generating unit is unavailable is called its forced outage rate (FOR). Given the LDC, individual unit capacities, and forced outage rates, the Baleriaux-Booth model can be used to compute the expected energy produced by each unit over the time period to which the LDC refers [24].

There are two key assumptions present in the Baleriaux-Booth model. The available capacity of each generator is assumed to be random and independent of other generators and the load. The generators are dispatched in a fixed, pre-assigned loading order, which does not depend on the time or history of usage (this loading order is not required to be the economic merit order) [22]. A more detailed discussion of the Baleriaux-Booth model can be found in [22] and [19].

The stochastic processes underlying the up and down states of the generating units and the load are not considered in this model. The resulting output is the expected cost, rather than a distribution of possible costs. For this reason, this model has been referred to as a probabilistic as opposed to a stochastic model. Since the cost function is non-linear, any hedging strategy that will minimize risks for market participants will need to consider the entire distribution of production costs. In spite of the limitations, the Baleriaux method appears to be appropriate for studies with long time horizons addressing issues of business policy and strategy [22].

The production cost method suffers from two main drawbacks. First, it requires detailed power system operational data, and secondly, they are complicated to implement and often have a high computational cost. Access to characterizing information about individual power systems is also complicated by its inherent proprietary nature [3]. An additional drawback is that the model lacks strategic bidding practices [23].

## 1.2 Heuristic and Statistical Methods

Heuristic methods are simple and used as comparative benchmarks for assessing the accuracy performance of any forecasting model. These methods use a first order curve fitting model to establish simple relationships between price and load. Examples of this are moving average, exponential weighted moving average, and the naive model [3].

Statistical models define the predicted variable in terms of a set of equations which involve some observed variables and disturbances. These models can be further divided into three categories: time series models, causal models, and stochastic models. For all types of statistical models, parameters are identified and estimated based on historical data. These methods try to predict price without modeling the underlying physical processes in detail. Models are classified based on the independent variables driving the model. Time series models model price as a function of previous price values. In structural or causal models, price is modeled as a function of other system factors such as load, fuel prices, etc [3]. Stochastic statistical models are a derived from financial models and adjusted to power market structure and behavior [6].

Alternatively, statistical methods can be categorized into linear and nonlinear methods. Linear statistical models tend to be based on assumptions of stationarity, which is defined as when the time series joint probability distribution does not change when shifted in time, and consequently whose mean and variance do not change when shifted in time. One of the most important and widely used linear statistical models is autoregressive integrated moving average (ARIMA) model, which has been applied successfully with regard to price and load forecasting. Non-stationarity is handled through several preprocessing methods including differencing, transformation, outlier removal, and intervention models. Other researchers have employed data clustering, variable segmentation and wavelet transform to non-stationary price series for use in stationary forecasting models [3].

Nonlinear methods include tools such as artificial neural networks, expert systems, fuzzy logic, and support vector machines. These methods tend to be flexible and can handle complexity and non-linearity, which makes them promising for short-term predictions. The main advantage of these techniques, especially artificial neural networks (ANN), is that they are capable of inferring hidden relationship in data [27]. Neural networks have been successfully used to forecast short-term load and price [14] [27]. ANN development is far from simple, and requires several steps specific to the inputs utilized and outputs desired. These steps include data preprocessing, neural network design, implementation, and validation. An extended review of these stages can be seen in [14]. Various techniques have been combined with ANN to offset weaknesses during these stages [16].

## 1.3 Medium to Long-term forecasting

Many data-driven electricity price forecasting approaches are mainly focused on short-term electricity price forecasting. This generally includes timescales from one hour-ahead to one day ahead. There has been less work on the medium term (weeks to years) and long term (many years) horizon. Additionally, since deregulation of electricity markets has began fairly recently around the world, limited explanatory data exist for medium and long term price forecasting. It is noteworthy that many of the forecasting engines such as artificial neural networks need a large data set for training, and thus are less applicable to medium and long term forecasting because of its availability [26]. Developing medium and long term forecasting is essential to many market activities, including generation expansion planning, maintenance scheduling, bilateral contracting, fuel contracting, and developing investment and hedging strategies. In particular, increased volatility in price means that the power industry has become more interested in risk management methods in all time horizons [25]. The situation becomes more complicated when comparing forecasts between several power markets. The dependability of cross hedging, or using futures contracts from different markets, as a risk-reducing instrument depends highly on the inter-market spot and future price correlation [5].

In general, there are three main steps involved in building a data-driven prediction model: data preprocessing, feature selection, and model selection. Data preprocessing aims at initial preparation of data and includes different tasks, such as data cleaning, data integration, data transformation, data reduction, and data discretization. In the context of electricity price forecasting, the most frequent used data preprocessing actions are outlier detection and manipulation, normalization, and data transformation [15]. Feature selection focuses on finding the most relevant and explanatory variable to use as inputs to the forecasting model. The best subset contains the least number of key features contributing to accuracy, while discarding the remaining unimportant features [4]. The last step is model selection, in which an appropriate forecasting engine is chosen. The choice is dependent upon many factors, such as data availability and various characteristics of the time series.

There are four important sources of data that can be used to develop long-run forecasts: historical electricity market prices, electric futures and forwards prices, simulation model results, and arbitrary judgment. Two common fundamental problems often lead to inferior forecasts. Forecasters rely almost entirely on financial data or engineering data, rather than utilizing both as information sources. Additionally, extrapolation of existing patterns does not incorporate future changes [13].

Financial data are limited largely by market immaturity and lack of data past 5-7 years out from present. Accuracy when these data are projected forward 20 to 30 years is questionable at best. Though engineering approaches offer detailed data, the validity of the results is rooted in the validity of the long-term forecasts. The problem with this approach is a strong tendency to understate the uncertainty in technology, system configuration, fuel prices, and demands. This results in a forecast that anchors on a very narrow range that can be inconsistent with market realities. Compounding these problems is the time and expense of running these models . Projecting patterns which stem entirely from the current system is risky, since the power industry is a dynamic and changing industry. A consolidated approach must focus not only on the details of the current system structure, but on the nature of the changes that will occur over the medium to long term timeframe [4].

## 1.4 Objective

We seek to create a computationally efficient production cost model with the following characteristics:

1) Reduce uncertainty of long-term parameter estimation.

2) Accurately characterize the effect of market pressures on power price.

CHAPTER 2

# METHODOLOGY

To determine optimal parameter estimation techniques, we compared simulated LMP with historical LMP in the ERCOT power market. Electricity generators were characterized by prime mover, fuel type, marginal cost, and capacity. Demand is system specific, and historical demand is publicly available through ERCOT. Location of generation, transmission, and demand was incorporated through a reduced system topology, courtesy of Altenex, LLC. A flow chart containing the steps to calculate LMP can be seen below in Figure 2.0.1. We discuss below the details of each aforementioned step

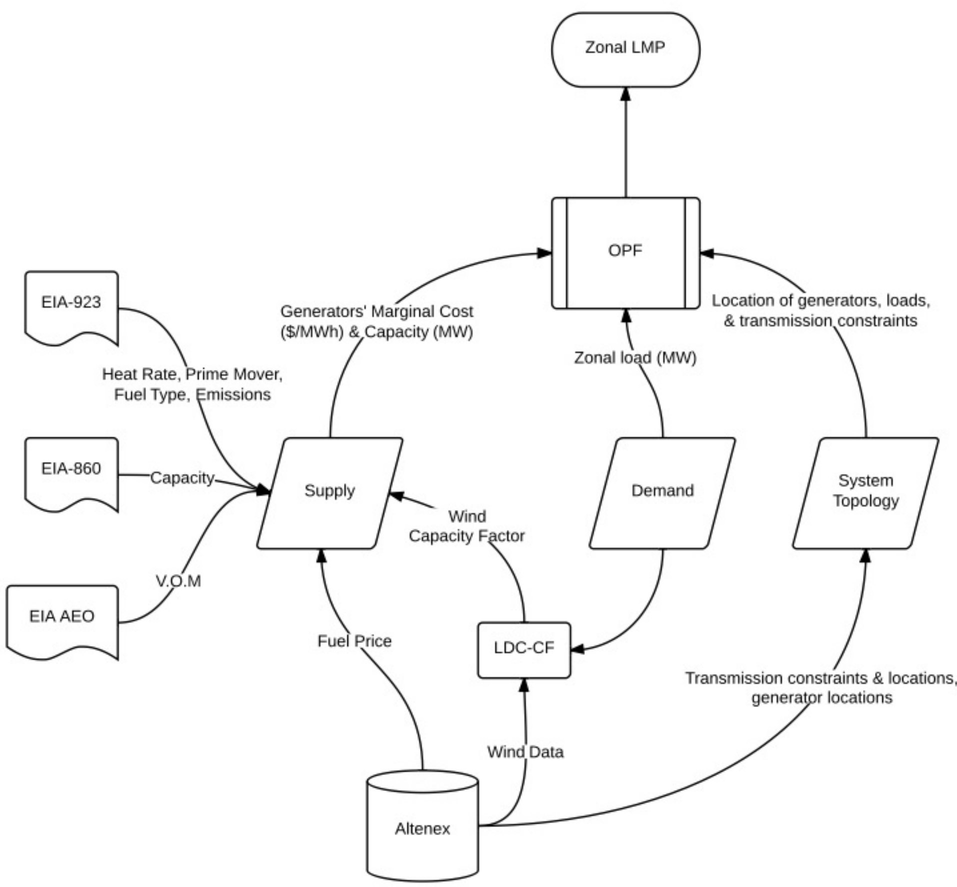


Figure 2.0.1: Flow Chart of Calculations and Information Sources

for the historical comparison to ERCOT, as well as for the parameter estimation method comparison.

## 2.1 Supply

In a centralized wholesale electricity market, generators submit bids to a dispatching authority which specify how much power the generator will deliver at what price. It is assumed that each generator bid includes one price and quantity, corresponding to the maximum amount of power the plant is capable of delivering and marginal cost of delivering said power. Our simulation assumes a perfectly competitive market, where the optimal bidding decision is exactly the marginal cost of power production.

### 2.1.1 Marginal Cost

Marginal cost (MC) is a function of fuel cost (FC), environmental cost (EC), and variable operations and maitenance (VOM), and can be calculated as:

$$MC_i^j = FC_i^j + EC_i^j + VOM_i^j \tag{2.1}$$

For each generator j at time i.

#### Fuel Cost

Fuel cost is equal to the product of heat rate (HR) and fuel price (FP). The heat rate of each generator is calculated by dividing the heat output of the plant by the net generation.

Net heat output and net generation at each month for each generator are taken from form EIA-923 for 2011 [9]. The equations for these parameters can be seen below:

$$HR_m^j = \frac{NetHeat_m^j}{NetGen_m^j} \tag{2.2}$$

For each generator j at month m.

$$FC_i^j = (FP_i^j)(HR_m^j) \tag{2.3}$$

For each generator j at time i, month m.

The fuel price is dependent on the fuel type of the plant. Fuel prices were calculated with units of $/BTU. The two main fuel sources in the ERCOT system were natural gas and coal. The burner-tip price is defined as the price which a generator pays for fuel, including regional cost differences based on a standard fuel spot price and transportation costs. For each zone, we calculated the fuel price as the sum of a standard fuel spot price and the difference between burner tip and the spot price, as seen below.

$$FP_i^k = SpotPrice_i^k + [BurnerTip_i^k - SpotPrice_i^k] \tag{2.4}$$

For each fuel type k at time i, Where k ∈ {Natural Gas, Coal}

Henry Hub price was used as a basis for natural gas [11], and Powder River Basin price was used as a basis for coal. Historical Powder River Basin prices and burner-tip data was provided by Altenex, LLC. For the rest of the fuel types, EIA data on average cost paid by electricity generators was used [10].

Due to data availability issues, start-up and ramp-up costs were not factored into the marginal cost.

**Environmental Cost**

Environmental cost is a function of marginal emission rate (MER) and cost per unit of emission (EP). Marginal emission rate (MER) is the total emissions divided by the amount of electricity generated. Estimates of carbon dioxide, methane, nitrous oxide, and sulfer oxide emissions for each generator are available in EIA-923. The ERCOT power market currently has no emission trading schemes. Therefore, in this analysis, the cost of emissions is set to zero.

$$MER_m^j = \frac{Gen_m^j}{NetEmissions_m^j} \tag{2.5}$$

$$EC_m^j = (MER_m^j)(EP_m) \tag{2.6}$$

**Variable Operations and Maitenance Cost**

Variable operations and maitenance costs dependent on the prime mover, fuel type, and specific technology used in the generator. Costs for natural gas and nuclear generators were taken from Table 1 in ”Updated Capital Cost Estimates for Utility Scale Electricity Generating Plants” published by EIA [12].

### 2.1.2 Capacity

Generator capacity is a function of nameplate capacity, availability, and capacity factor. We define availability factor (AF) as the percentage of time the reactor is operational over the course of a year. Availability is assumed to be 100% for all generators. The nameplate capacity is taken from EIA-860 for Generators [8]. Nameplate capacity from

EIA-860 is given with an associated Plant ID, prime mover, and fuel type. As capacity data is not available for all units listed in form EIA-923, in this analysis, only plants which had capacity data available which matched its prime mover and fuel type were included.

Capacity factor (CF) was assumed 100% for all plants except for hydroelectric and wind powered generators. For hydroelectric plants, capacity factor was assumed to be a function of month. Historical capacity factors were calculated for each plant based on generation reported in EIA-923 and rated capacity from EIA-860. The plant capacities were then de-rated according to the product of the calculated monthly capacity factor times the rated capacity. This effective capacity was the generating capacity which the hydroelectric plants bid into the supply stack. Equations describing these calculations can be seen below:

$$Capacity_i^j = (NameplateCapacity)(AF)(CF) \tag{2.7}$$

For generator j at time i.

$$AF = \begin{cases} 1, & \text{if } Gen_m^j > 0. \\ 0, & \text{otherwise.} \end{cases} \tag{2.8}$$

For generator j at month m.

### Wind Capacity Factor

Capacity factor for wind was calculated as a function of zonal load. The premise was supported by a consistent, but low negative correlation between historical load and wind capacity factor. These correlation coefficients for 2011 can be seen below in Table 2.1

Table 2.1: Correlation between Zonal Load and Wind Capacity Factor

| Zone | Correlation |
|---|---|
| North | -0.2818 |
| South | -0.2635 |
| West | -0.2344 |
| Houston | -0.2470 |

Historical hourly wind generation for a representative site in ERCOT North was provided by Altenex, LLC. Load at each zone was grouped into N bins. The corresponding wind capacity factor at each load point in the bin was collected in a separate vector. The aggregate vector of wind capacity factors was averaged across each load bin to create a single average wind capacity factor at each bin. This calculation is performed for each zone. The capacity factor of the wind in each zone is adjusted based on which bin the load corresponds to at each point. The adjusted aggregate supply stack is then used as an input to the OPF solver. A plot of the average resulting wind capacity factor at each hour for each month in ERCOT North can be seen below in Figure 2.1.1 and in Figure A.1.2.

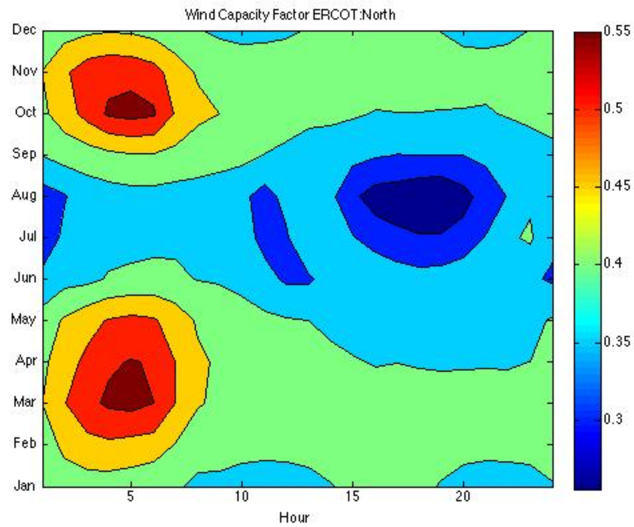


Figure 2.1.1: 12x24 Wind Capacity Factor: ERCOT North

## 2.2 Electricity Demand

The demand for electricity determines the commitment of generators and resulting power price. Due to lack of utility scale storage, demand must be instantaneously met. We assumed in this model that electricity demand was inelastic. Historical electricity demand is available from ERCOT and is reported on an hourly basis. Demand was broken up by load zones created by ERCOT. To follow the four bus model, we consolidated the zones in the following way:

ERCOT North = North Coast + East

ERCOT South = Southern + Southern Coast

ERCOT West = Far West + West + North

ERCOT Houston = Coast

## 2.3 Topology

ERCOT can be divided into four regions: North, South, West, and Houston. We simplified the topology of the ERCOT power market to a four-bus system to represent the aforementioned regions. Plant location data from EIA and geospatial software was used to sort all of the generators into four zones. Simplified transmission constraints corresponding to the four-bus model are given by Altenex, LLC. Since ERCOT contains relatively little intermarket transmission capacity, we do not include it in this model.

## 2.4 Optimal Power Flow

The model creates a unique aggregate supply stack at each hour for each bus. This information, in addition to the load and transmission constraints, are inputs to MATPOWER, an optimal power flow solver [28]. MATPOWER is an open-source Matlab-based power system simulation package, used widely in research and education for AC and DC power flow and optimal power flow simulations.

MATPOWER employs the standard OPF formulation:

$$\min_{x,z} f(x) + f_u(x, z))$$

subject to the following constraints:

$$g(x) = 0$$

$$h(x) \leq 0$$

$$x_{min} \leq x \leq x_{max}$$

$$l \leq \begin{bmatrix} x \\ z \end{bmatrix} \leq u$$

$$z_{min} \leq z \leq z_{max}$$

We do not include any ancillary market, interregional effects, or strategic gaming effects. The output of the script is hourly power dispatch and zonal clearing prices.

# CHAPTER 3

## RESULTS

It is important to note that model is intended for forecasting long-term trends and characterization of market responses to changing pressures, and is not appropriate for hourly price forecasting. It is important to evaluate our results at the resolution which is appropriate for the intended purpose of the model. In order to quantify the general magnitude and trends of our percent error, we must reduce the impact of price spikes on the resulting percent error. To accomplish both of these goals, we calculate for each month the median forecasted and historical prices at each hour. We can then compare the historical and simulated median prices, and calculate a percent error of the median prices at each hour in each month. We then take the absolute value of the percent error of the medians and average them to get a MAPE value at each month. The temporal resolution at which historical accuracy is compared to has a significant effect on both magnitude of percent error and parameter estimation accuracy. Equations describing the aforementioned parameters can be seen below:

Let $\overline{LMP}_{m,h}$ denote the median of the LMP at month "m" and hour "h"

$$PE_{m,h} = \frac{\overline{LMP}^{hist}_{m,h} - \overline{LMP}^{sim}_{m,h}}{\overline{LMP}^{hist}_{m,h}} \tag{3.1}$$

$$APE_{m,h} = |PE_{m,h}| \tag{3.2}$$

$$MAPE_m = \frac{1}{H}\sum_{h=1}^{H}(APE_{m,h}) \tag{3.3}$$

We seek to test two important parameter estimation techniques in the model. The first of which is the availability factor method, in which generators which produce no electricity for a month according to EIA-923 are excluded from the supply stack. The second parameter estimation method we seek to evaluate is the wind capacity factor method. We will refer to the trial with both original methods for capacity factor of wind and heat rate calculation as *Case 1*. We will refer to the trial with a static capacity factor for wind as *Case 2*. *Case 3* will implement the heat rate calculation by averaging instead of elimination from the supply stack.

We first estimate mean absolute percent error (MAPE) of the predicted prices at a monthly time scale. At the monthly time scale, the three cases performed essentially the same for all zones and all months. We encounter MAPE values bounded between 5% and 267%. Plots of the MAPE for each zone can be seen in the Appendix B.2.

To compare the performance of the two alternate cases (AC) to the base case (BC), we subtract the percent error of the base case from the percent error of each of the alternate cases, as seen below:

$$\Delta PE^{i}_{m,h} = PE^{AC_i}_{m,h} - PE^{BC}_{m,h} \tag{3.4}$$

For alternate cases 2 and 3, at month “m” and hour “h”.

Accordingly, a positive value for the difference implies a better performance by the base case, and vice versa. For all simulations, the most visible trend was an underestimation of the day time hours during the autumnal months, and an general overestimation of night time prices. Excluding the startup and ramping costs from the marginal costs has been shown to have the largest effect during high and low load events [21], and may be a contributing factor to this systemic error. The results of the comparison are best visualized via contour plot, and can be seen in Appendix C.

Hypothesis testing was needed to compare performance. To pick an appropriate statistical test, we needed to determine whether the data belonged to a standard normal distribution. We used a one-sample Kolmogorov-Smimov test and determined that none of our samples were normally distributed. Therefore, to conclude whether the base case performed better than the trial cases and vice versa, we used a Wilcoxen Rank-Sum test. The results of the hypothesis tests can be seen in the following sections.

### 3.0.1 Effect of Availability Factor Method

The current model has the benefit of utilizing historical data to estimate availability. To do this, we remove from the corresponding month's supply stack any plant which reports a zero heat rate for that month. The resulting availability factor can be seen below in Figure 3.0.1.

To compare the effectiveness of this estimation method, we created a separate trial with a different method. In the separate trial, we replace a zero heat rate entry with an average heat rate for each plant based on the respective plant's heat rates in other months. If a plant reports a zero heat rate for all months of the year, it is excluded from all supply calculations.

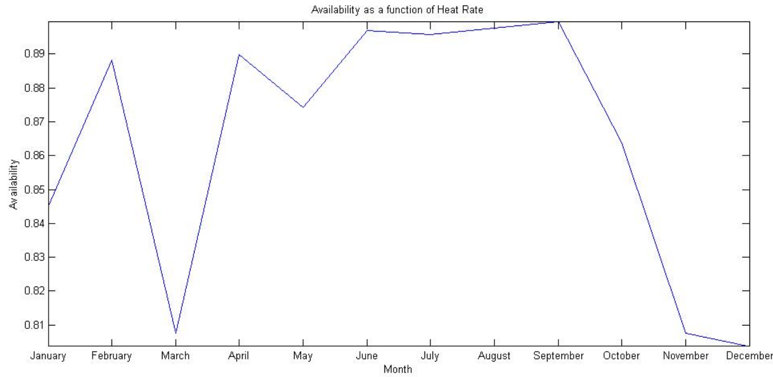


Figure 3.0.1: Availability Factor

The percent errors of the two trials were compared by subtracting the percent errors of the base case from the percent errors of the alternate case. The contour plot of the difference in percent errors for each zone can be seen in Appendix C.

The first test we ran had a null hypothesis that the median of the differences of the percent errors of the two cases was equal to zero. The alternate hypothesis was that the median was not equal to zero. We were able to reject the null hypothesis for all four zones at the $\alpha = 5\%$ level. This indicates that the cases did perform differently. We used a one-tailed test to test with an alternate hypothesis that the difference of the median percent errors was greater than zero, indicating that the base case performed better than the trial case. We were able to reject the null hypothesis at the $\alpha = 5\%$ level for all four zones, which indicates that the base case performed better for all zones.

### 3.0.2 Effect of Load-Based Wind Capacity Factor Method

We utilize a novel method to estimate wind capacity factor in our base case. The capacity factor is adjusted at each load point based on the corresponding average capacity factor at the respective load bin. To visualize the effect of this method on capacity factor, we have created contour plots with the average capacity factor at each hour for each month for all zones. These contour plots can be seen in the Appendix. Concurrent with general weather trends, we see higher wind capacity factors during the night time hours in the winter, and lower wind capacity factors during the daylight hours in the summer. To compare the effectiveness of this method, we compared the median percent error of the base case with that of a trial case in which the capacity factor of wind in the ERCOT system was assumed to be 35%.
The percent errors of the two trials were compared by subtracting the percent errors of the base case from the percent errors of the alternate case. The contour plot of the difference in percent errors for each zone can be seen in the Appendix C..

The first test we ran had a null hypothesis that the median of the differences of the percent errors of the two cases was equal to zero. The alternate hypothesis was that the median was not equal to zero. We were able to reject the null hypothesis for all four zones at the $\alpha = 5\%$ level. This indicates that the cases did perform differently. We used a one-tailed test to test with an alternate hypothesis that the difference of the median percent errors was greater than zero, indicating that the base case performed better than the trial case. We were unable to reject the null hypothesis at the $\alpha = 5\%$ level for all four zones, which indicates that the base case did not perform better than the trial case for all zones. We then changed the alternate hypothesis to test whether the trial case performed better than the base case. We were able to reject the null hypothesis at the $\alpha$

= 5% level for all four zones, which indicates that the trial case performed better than the base case for all zones.

### 3.0.3 Conclusion

#### Summary

Production cost models can provide system operators and market participants with useful insight into market dynamics and responses to changing pressures and scenarios. Understanding the resolution which is necessary to produce the desired analysis is crucial. Increasing the resolution of the model may result in increased accuracy, but can add considerable hurdles in terms of data gathering, computational cost, and uncertainty considerations. Production cost models are limited by access to technical information, as well as by future market and policy changes.

Availability of generators is a crucial parameter in price forecasting, and has a significant effect on the resulting market clearing price. The magnitude of this effect depends on the distribution of marginal prices of generators at each zone, as well as the system load.

The importance of parameter accuracy depended on zone. Accuracy of price estimation in the North and South zones was impacted more by the availability factor method, while accuracy in the West and Houston zones was impacted more by the wind capacity factor method.

For all cases, we observed underestimation of LMP during peak summer hours, and overestimation of LMP during summer nights.

Using a Wilcoxen-Ranksum test, we were able to determine that Case 2 performed better than the base case at the $\alpha = 5\%$ level. We were able to determine that Case 3 performed worse than the base case at the at the $\alpha = 5\%$ level.

**Future Work**

There are several parameter estimation methods in the model which require further investigation. The current method to estimate wind capacity factor utilizes one representative site to determine the wind behavior for all zones in the system. If data is available, it may improve accuracy to use geographically representative wind sites for each zone. Additionally, the associated capacity factor was created by binning the loads on a yearly basis. It may be an improvement to create a unique capacity factor assignment for each month, depending on the monthly distribution of loads and capacity factor. Furthermore, one representative site may not be a good representative of the zone in question. An array of function transformations should be tested to find the optimal shape characterizing wind behavior in the respective zone. Although we found no improvement utilizing the wind capacity factor estimation method, wind capacity factor may have significant impact in systems with higher wind penetration.

Several exclusions to the model may have introduced systemic error into the price forecasts during high and low load events. These exclusions include ramping and startup costs, congestion rates, and strategic bidding methods.

The method in which availability was calculated for historical comparison will not be able to be applied to forecasting. A new availability estimation technique will need to be developed.

As it is, the model is highly parallelizable. Additional parameter estimation methods should weight the tradeoff of accuracy increases with corresponding performance decreases. Potentially time-dependent parameters like ramp rate and ramp cost should be calculated with this in mind. A potential method to characterize the effect of ramping rates is utilizing a heuristic shape adjustment, based on historical error. Care should be taken to create a robust method to forecast this shape adjustment in a changing market.

The ultimate use for this model will depend on what market scenarios and level of detail is demanded. It is possible that the computational cost of this model can increase or decrease. Unless substantial changes are made, we remain with a relatively expensive objective function and a large number of potential scenarios of interest. Response surfaces may help characterize the objective function space, and its dependence on the many variables of interest. This may allow for greater insight into market dynamics with significantly lower computational cost. Given enough CPU time, a thorough characterization of market dynamics may be possible.

Given reasonable confidence in performance compared to historical power price, other power systems should be similarly characterized. Intermarket transmission should be factored into the market topology. Many parameters will be market and location dependent, and care should be taken to accurately characterize each marketplace's independent variables.

In the long term, plant retirement and new generation, load evolution, and other parameters must be factored into forecasts. Uncertainty on this time scale may be reduced by Monte-Carlo simulation over a distribution of likely scenarios.

APPENDIX A

**WIND CAPACITY FACTOR ESTIMATION**

## A.1 ERCOT North

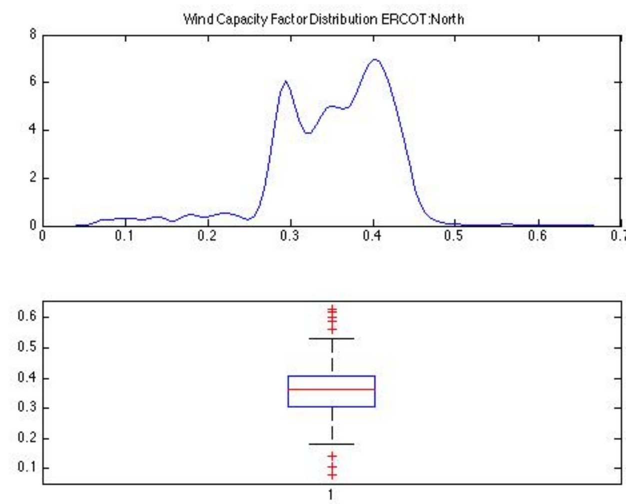


Figure A.1.1: PDF and Boxplot Wind Capacity Factor: ERCOT North

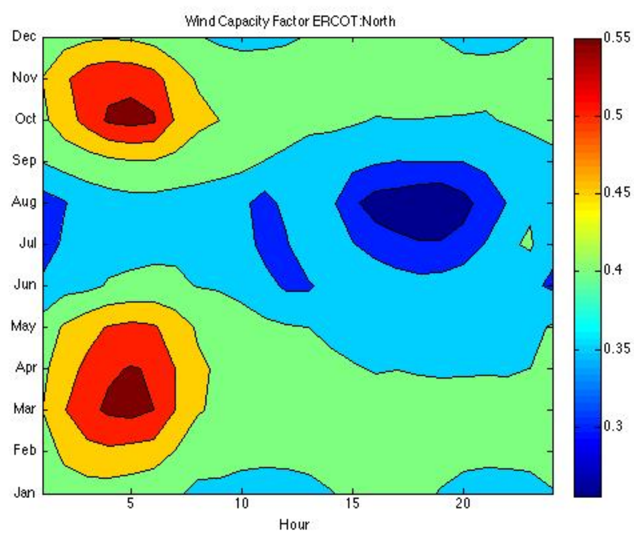


Figure A.1.2: 12x24 Wind Capacity Factor: ERCOT North

## A.2 ERCOT South

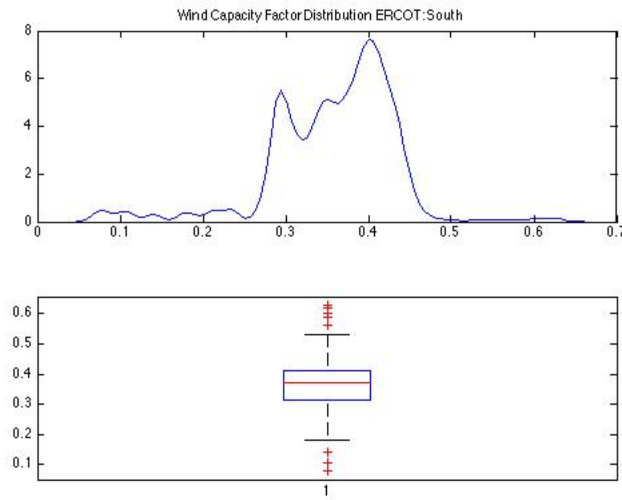


Figure A.2.1: PDF and Boxplot Wind Capacity Factor: ERCOT South

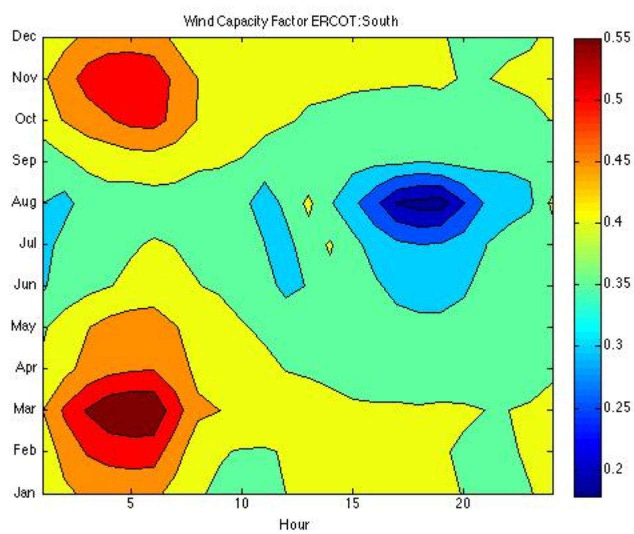


Figure A.2.2: 12x24 Wind Capacity Factor: ERCOT South

## A.3 ERCOT West

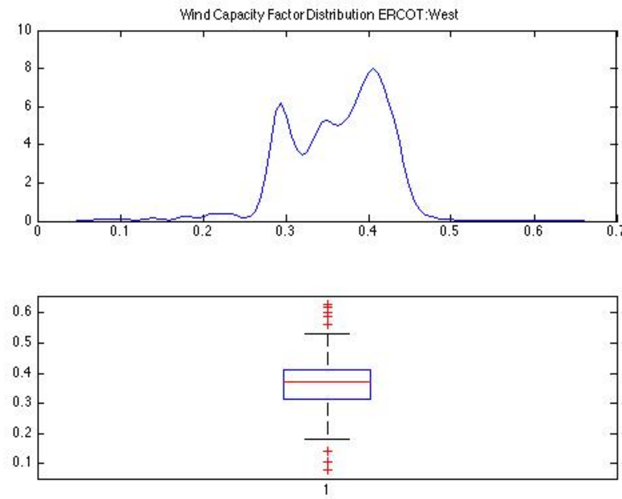


Figure A.3.1: PDF and Boxplot Wind Capacity Factor: ERCOT West

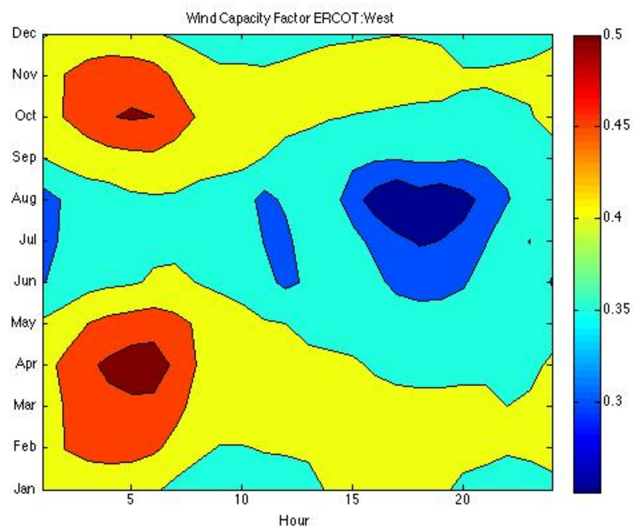


Figure A.3.2: 12x24 Wind Capacity Factor: ERCOT West

## A.4 ERCOT Houston

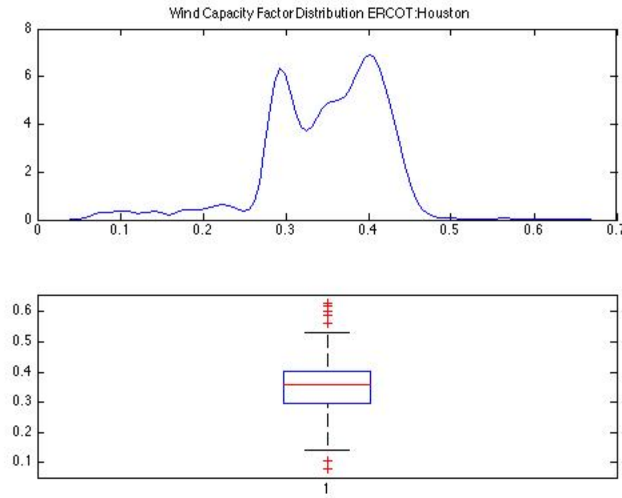


Figure A.4.1: PDF and Boxplot Wind Capacity Factor: ERCOT Houston

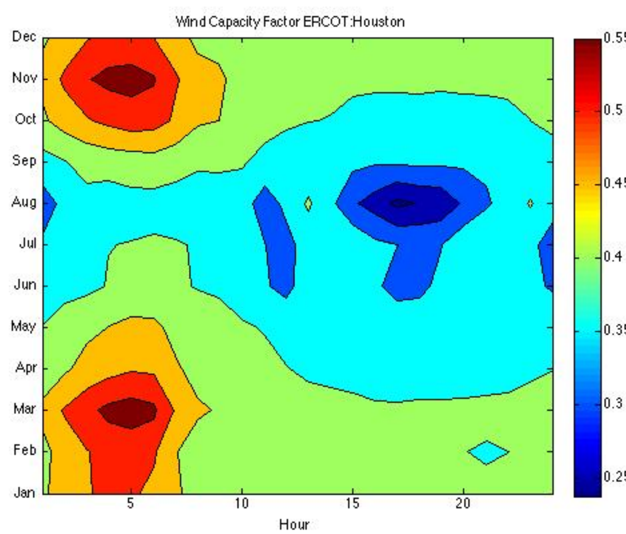


Figure A.4.2: 12x24 Wind Capacity Factor: ERCOT Houston

APPENDIX B

# COMPARISON TO HISTORICAL PRICE

We compare three cases. Case 1 is the base-case model. Case 2 is the trial with a static wind capacity factor of 35%. Case 3 is the trial where a zero heat rate entry is replaced with a mean heat rate for that specific generator when available.

## B.1 12x24 Percent Error of Median

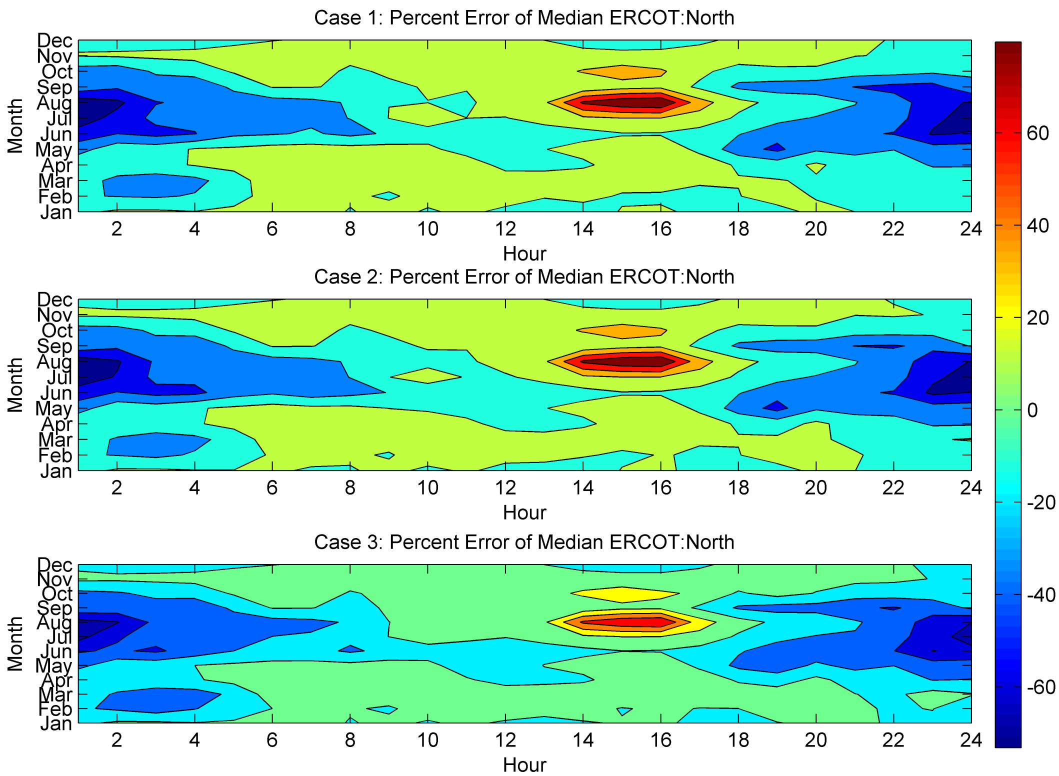


Figure B.1.1: Percent Error of Median: ERCOT North

Underestimation of historical LMP up to about 60% is observed during the summer afternoon hours. Overrestimation of historical LMP up to about 60% is observed during the summer evenings.

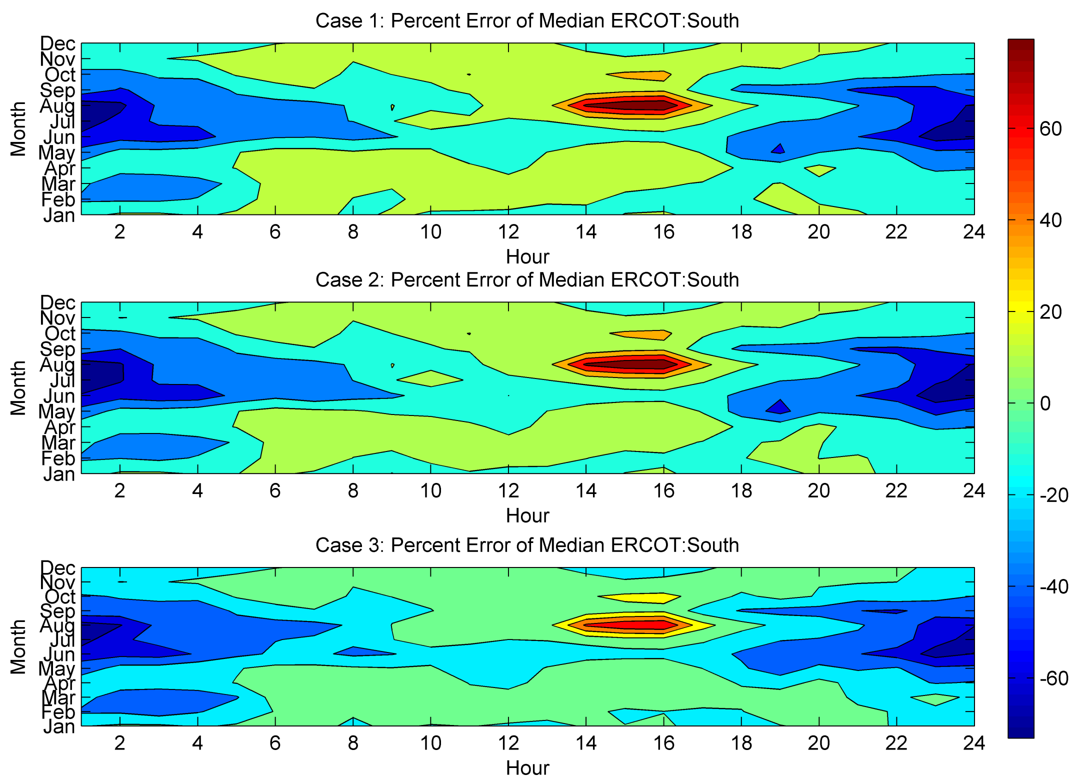


Figure B.1.2: Percent Error of Median: ERCOT South

Underestimation of historical LMP up to about 60% is observed during the summer afternoon hours. Overrestimation of historical LMP up to about 60% is observed during the summer evenings.

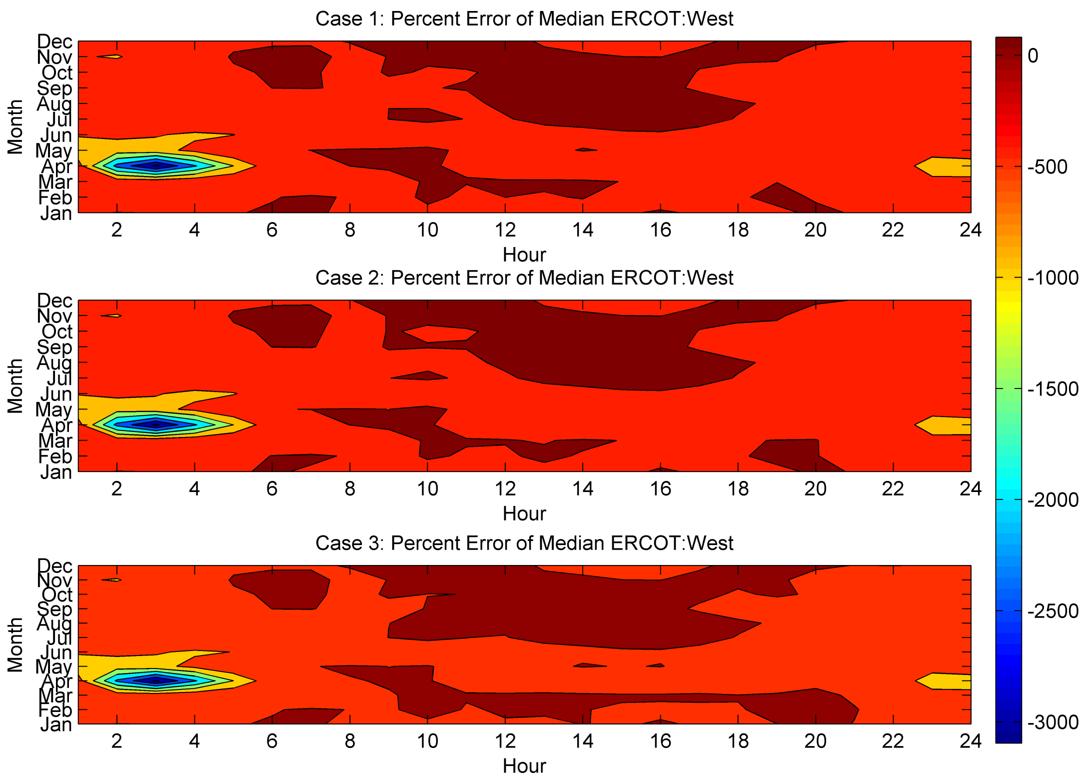


Figure B.1.3: Percent Error of Median: ERCOT West

The presence of outliers and price spikes distorts most meaningful analysis for ERCOT West.

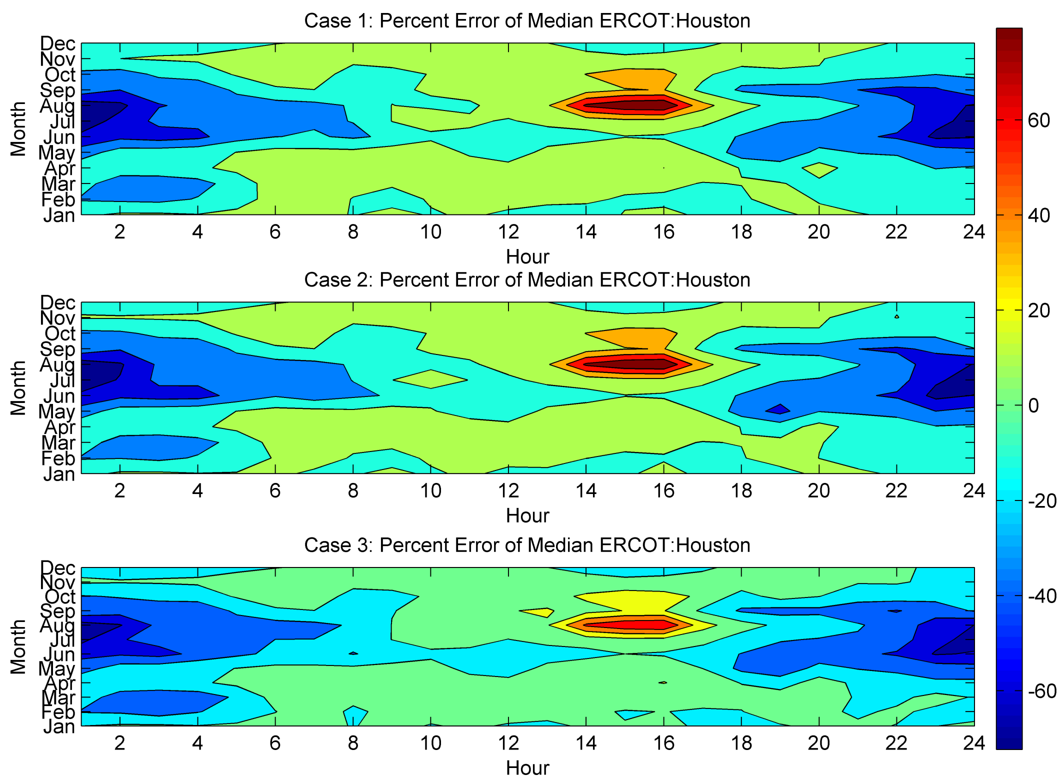


Figure B.1.4: Percent Error of Median: ERCOT Houston

Underestimation of historical LMP up to about 60% is observed during the summer afternoon hours. Overrestimation of historical LMP up to about 60% is observed during the summer evenings.

## B.2 MAPE of Percent Error of Median

MAPE was taken for each month. The two values compared to calculated MAPE were the median of historical prices for each hour at each month and the comparative values for all three cases. No significant MAPE differences were found between the three cases at this resolution.

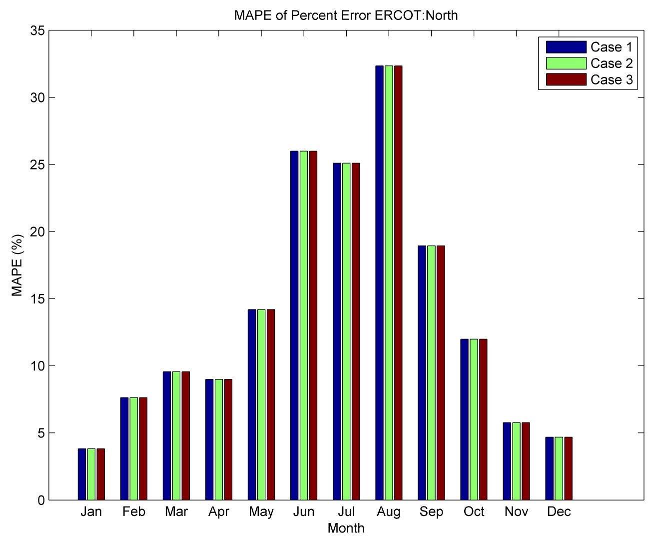


Figure B.2.1: MAPE of Percent Error: ERCOT North

MAPE range from about 5% in the winter months and steadily increases to around 30% in the summer months.

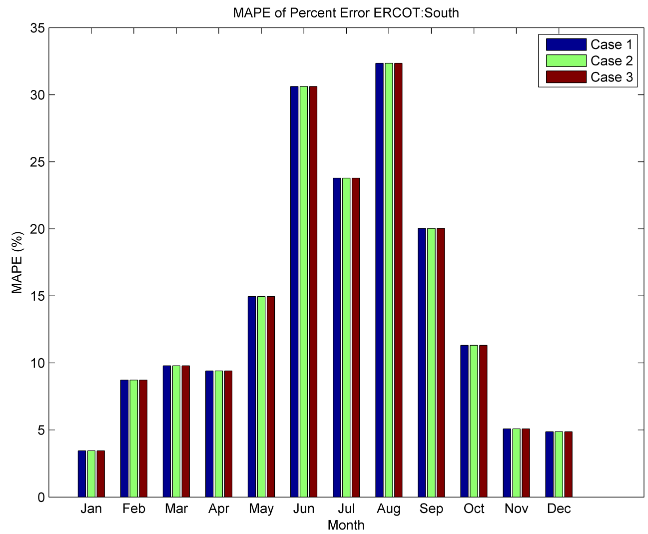


Figure B.2.2: MAPE of Percent Error: ERCOT South

MAPE range from about 5% in the winter months and steadily increases to around 30% in the summer months.

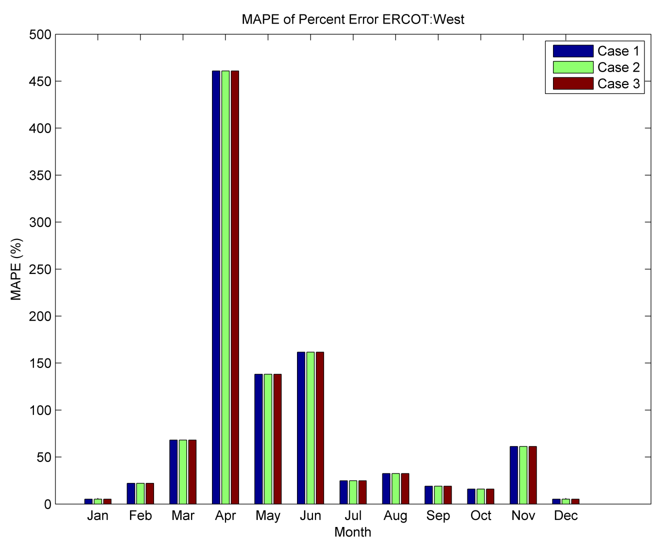


Figure B.2.3: MAPE of Percent Error: ERCOT West

MAPE range from under 15% in the winter months. Price volatility significantly effects MAPE, most notably during the spring, but to a lesser degree during the summer months.

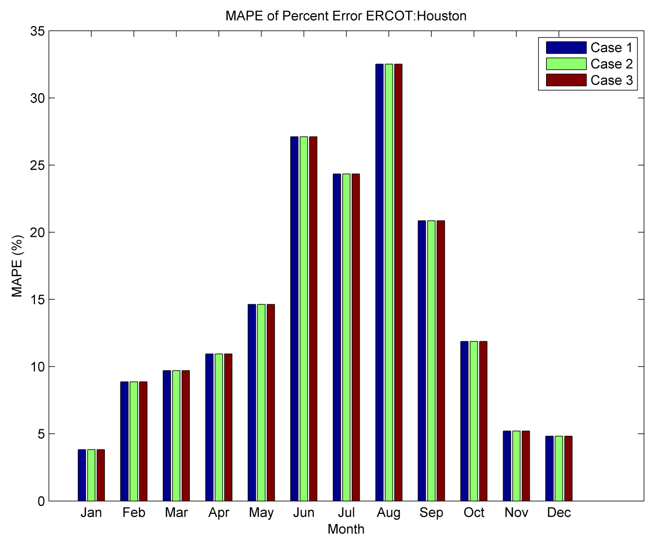


Figure B.2.4: MAPE of Percent Error: ERCOT Houston

MAPE range from about 5% in the winter months and steadily increases to around 30% in the summer months.

APPENDIX C

# CASE COMPARISON

We compare the relative performance of case 2 and 3 to case 1 by taking the difference of the percent error of median prices. A positive value indicates a lower percent error in case 1, compared to the alternate case in question, and therefore a better performance. A Wilcoxen Ranksum test indicates that Case 2 performed better than the Base Case, and that Case 3 performed worse than the Base Case.

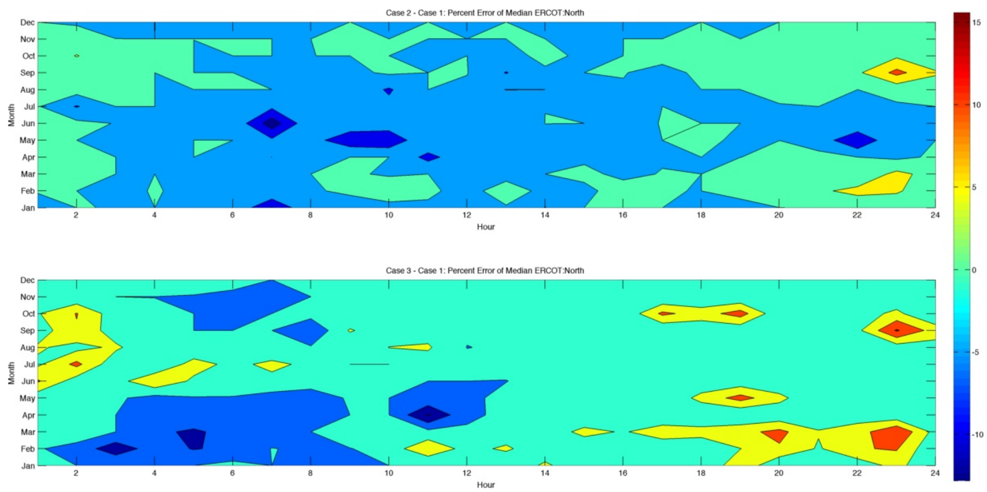


Figure C.0.1: Comparison of Cases to Base Case: ERCOT North

In the Case 2 comparison to Case 1, we notice an improvement utilizing the LDC-CF method during the most of the night-time hours compared to a static wind capacity factor. In the Case 3 comparison to Case 1, we notice significant error during mornings and evenings.

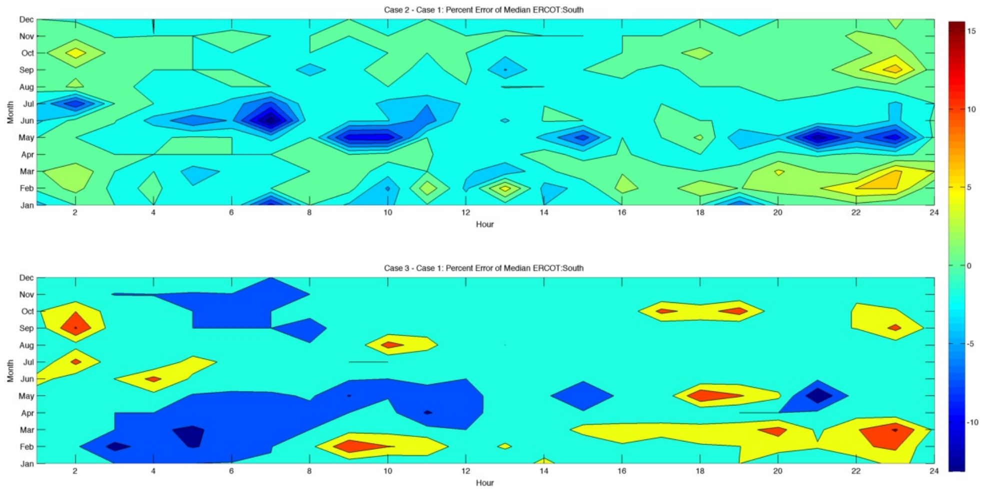


Figure C.0.2: Comparison of Cases to Base Case: ERCOT South

In the Case 2 comparison to Case 1, we notice an improvement utilizing the LDC-CF method during the most of the night-time hours compared to a static wind capacity factor. In the Case 3 comparison to Case 1, we observe sporadic differences in error during all hours.

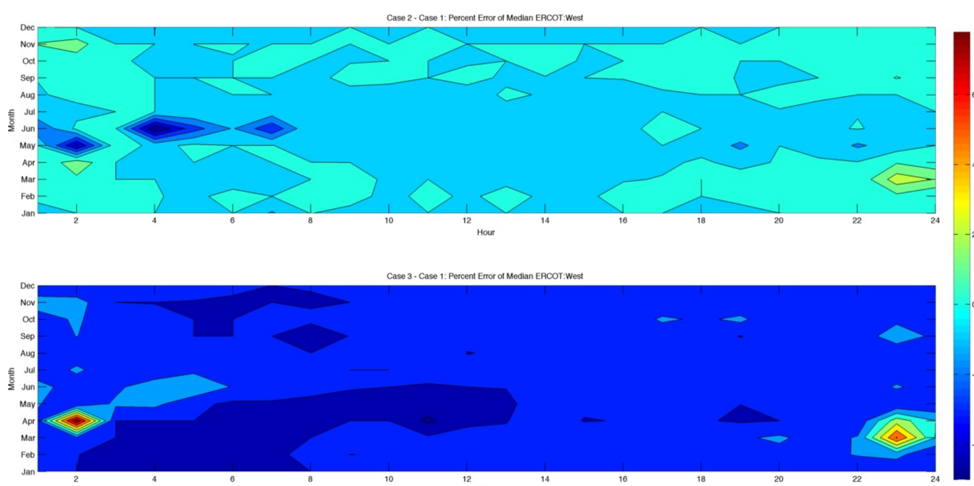


Figure C.0.3: Comparison of Cases to Base Case: ERCOT West

The presence of outliers due to price spikes obscures most meaningful analysis.

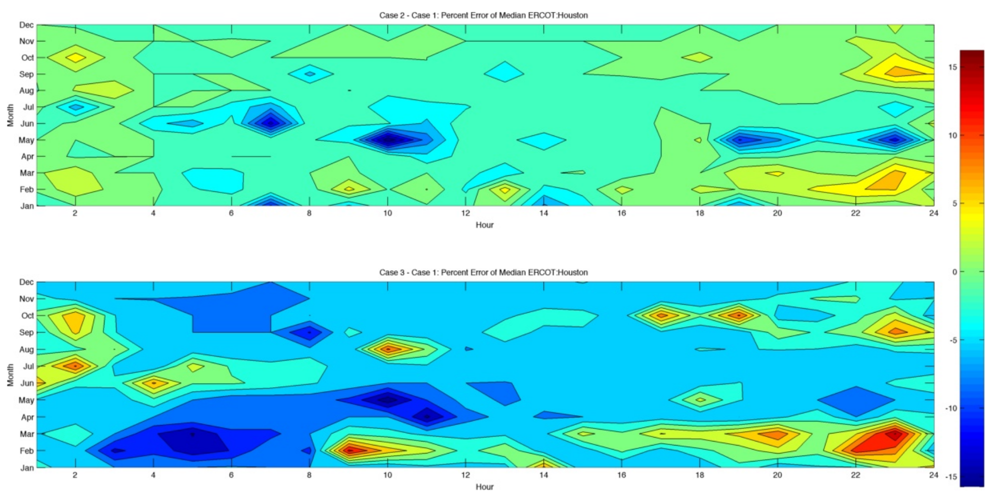


Figure C.0.4: Comparison of Cases to Base Case: ERCOT Houston

In the Case 2 comparison to Case 1, we notice an improvement utilizing the LDC-CF method during the most of the night-time hours compared to a static wind capacity factor. In the Case 3 comparison to Case 1, we observe sporadic differences in error during all hours.

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